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SUMMARY

Background

Accidents are a common cause of lost duty time and physical disability separations among U.S. Navy personnel. U.S. Navy occupations with high rates of on-duty accidents also tend to have high rates of off-duty accidents. This general tendency to have high rates of accidents in both settings has led to the suggestion that some occupations have high accident rates because they attract individuals whose personality includes high risk taking tendencies.

Objective

This paper compared the personality trait explanation for the correlation between on-duty and off-duty accident rates to an occupational learning perspective. Drawing on research on judgment and decision making, the occupational learning model predicted that people in hazardous occupations learn to take risks on-duty and off-duty because their work experiences bias their judgments in ways that reduce the perceived risk of any given activity.

Approach

Ratings of occupational demands for physical exertion (physical demands, PD), quick recognition of and response to signals in the work environment (reaction time, RT), sound logic in complex information processing (reasoning, R), good communication skills (communication, C), and quick, dextrous movements (dexterity, D) were taken from data reported by Reynolds, Barnes, Harris and Harris (1992). Those researchers obtained ratings for entry level jobs from senior enlisted personnel in 57 U.S. Navy occupations for which Ferguson, McNally, and Booth (1985) provided data on both on-duty and off-duty accident rates. Correlation and regression analyses were used to evaluate the relationships between job demands and accident rates. TETRAD analysis tested the hypothesis that the overall pattern of associations could be explained by a model with a single factor.

Results

Occupational demands predicted both on-duty and off-duty accident rates. PD ratings were the only predictor that was more strongly related to one accident rate than to the other ($r_{On\text{-}Duty} = .792 > r_{Off\text{-}Duty} = .547$). The multiple regression equations for on-duty and off-duty accident rates both included PD and RT as predictors. The partial correlation (*pr*) between on-duty and off-duty accident rates controlling for PD and RT was much smaller than the simple bivariate correlation ($pr = .164$ vs. $r = .567$) and was statistically nonsignificant. The semipartial correlations (*srs*) indicated that on-duty accident rates accounted for less than 1% of the variance in off-duty accident rates controlling for PD and RT. The TETRAD analysis indicated that two of the three implied tetrad equations were not supported by the data.

Conclusions

The occupational learning model fit the data better than the personality trait model. Occupational conditions accounted for better than 97% of the overlap between on-duty and off-duty accident rates, leaving little residual association to be explained by a trait of risk taking. The TETRAD analyses indicated that the trait model could not account for the observed pattern of associations.

The findings have implications for accident reduction programs. If accidents depend on preexisting personality traits, accident reduction will require that people with high risk-taking tendencies be assigned to low-risk jobs. Adding another constraint to the existing assignment process would exacerbate the already complex problem of optimizing assignments. Also, assigning people who like taking risks to what they perceive as boring low-risk jobs could increase retention problems.

The occupational learning perspective offers alternatives that could augment or refine existing accident reduction training programs. The occupational learning perspective was based on well-known biases in human judgment processes. Effective training methods to reduce the effects of those biases have been developed and could be adapted for use in accident reduction programs.

Introduction

U.S. Navy occupations with high on-duty accident rates tend to have high off-duty accident rates (Ferguson, McNally, & Booth, 1985; Helmkamp & Bone, 1986). The association between on-duty and off-duty rates suggests that these rates share one or more common causes (Heise, 1975; Glymour, Scheines, Spirtes, & Kelly, 1987).

Individual differences in risk taking (Ferguson et al., 1985) and lifestyle (Hansen & Pedersen, 1996) have been suggested as causes that could affect both rates. These suggestions assume that the person brings risk-taking tendencies to the job. Ferguson et al. (1985) support this view by noting that personality influences occupational choices (Holland, 1985). This report contrasts this individual differences perspective on risk taking with an occupational learning perspective based on the assumption that exposure to risk on the job teaches people to take more risks.[1]

Recruits are not finished products when they enter the service. Longitudinal studies of personality development (e.g., Haan, Millsap, & Hartka, 1986; Helson & Moane, 1987) and cross-sectional norms for standardized personality inventories indicate substantial personality change from the late teens up to about 30 years of age (Costa & McCrae, 1992; Greene, 1991, pp. 44-47; see also McCrae & Costa, 1990). This age range covers the full period of military service for the typical U.S. Navy recruit who enters the service between the ages of 17 and 21, serves a single four- to six-year enlistment, and leaves the service before the age of 30. The period from 18 to 30 years of age also is a major portion of the total service time even for recruits who remain in the Navy until retiring 20 to 30 years after enlisting. Thus, ongoing personality development is the norm for U.S. Navy enlisted personnel.

Occupational experiences can influence the direction and magnitude of personality changes (Kohn & Schooler, 1973). An argument that general risk-taking propensities are affected by occupational experiences can be made. The argument begins with the suggestion that risk taking is one aspect of health behavior (Vickers, Conway, & Hervig, 1990). If so, the Health Belief Model (HBM; cf., Janz & Becker, 1984) provides a theoretical basis for predicting accident-related behaviors. The assumption that people avoid activities that have a high probability of producing severe illness is central to the HBM.

The HBM is one of a family of expected value models that provide a normative definition of rational decision making (Edwards, Lindman, & Savage, 1963; Mitchell 1974). The expected value of a behavior is determined by the subjective value of different outcomes and the probability that performing the behavior will produce each outcome. Outcomes can be positive or negative and the overall value of a behavior is the sum of the outcome valences times their respective probabilities. Given a choice between different behaviors, the person is expected to choose the behavior with the highest expected value.

The family of expected value models has stimulated extensive judgment and decision making research. The cumulative evidence clearly indicates that people are not strictly rational when compared to this

normative framework. The systematic differences between the normative prescriptions of rational decision models and actual behaviors have been characterized as heuristics and biases (Kahneman, Slovic, & Tversky, 1982; Evans, 1989; Tversky & Kahneman, 1973). The present discussion focuses on one heuristic, the availability heuristic, to establish a plausible basis for predicting that on-duty occupational exposure to risk can lead to greater off-duty risk taking.[2]

The availability heuristic invokes memory and recall as the bases for judgments. In particular, the availability heuristic can be defined as follows: "There are situations in which people assess the frequency of a class or the probability of an event by the ease with which instances or occurrences can be brought to mind. . . . This judgmental heuristic is called availability." (Tversky & Kahneman, 1973).

A sailor in a high-risk occupation can be expected to build up a large store of memories of instances in which risks have benign consequences. Even in occupations with high accident rates, accidents occur only a small percentage of the times that any given task is performed. People in risky occupations perform such risky tasks more often than people in low-risk occupations. People in high-risk occupations, therefore, store more memories of safely completing hazardous tasks. The larger memory store should increase the ease with which people in high-risk occupations can recall instances of successfully completing a risky task. Other things equal, the availability heuristic will convert those memories into lower judged probabilities of having accidents.[3]

The availability heuristic also can reduce the judged severity of injuries. Most injuries to U.S. Navy enlisted personnel are minor, as indicated by the fact that injuries treated on an outpatient basis are 20 to 40 times more common than accidents requiring hospitalization.[4] Only about 10% of accidents treated on an outpatient basis cause the person to lose time from work (Krentz, Li, & Baker, 1997). Also, people almost certainly do not even seek medical care for many minor injuries. Thus, severe accidents are rare compared to minor injuries. A person working in a hazardous occupation will observe more minor injuries than a person in a less hazardous occupation. Ease of recall of minor injuries will increase for the person in the hazardous occupation, thereby yielding lower injury severity ratings than expected from people in less hazardous occupations.

Consideration of the availability heuristic in relation to the HBM can account for the correlation between on-duty and off-duty accident rates. If what is learned on the job generalizes to other settings, the judgmental biases learned from job experiences will be a shared causal influence for on-duty and off-duty accidents. Sharing a causal influence implies that the two accident rates will be correlated (Heise, 1975; Glymour et al., 1987).

The preceding reasoning leads to testable hypotheses. The hypotheses contrast the common view that risk-taking tendencies are a behavioral trait that the individual brings to the job with the view that risk-taking tendencies develop on the job as a result of occupational learning. If the occupational learning interpretation is viable, occupational conditions should predict both on-duty and off-duty acci-

dent rates. Also, controlling for occupational differences in occupational hazards should reduce or even eliminate the correlation between on-duty and off-duty rates (Heise, 1975; Glymour et al., 1987). This study combined Ferguson et al.'s (1985) accident data with Reynolds, Barnes, Harris, and Harris' (1992) ratings of occupational demands to test these hypotheses.

Method

Sample

Ferguson et al. (1985) reported accident rates for 68 U.S. Navy occupations, 57 of which had been included in the Reynold's et al. (1992) study of occupational demands. Those 57 occupations were the sample for this study.

Occupational Condition Ratings

Occupational demand ratings were taken from Reynolds et al.'s (1992) Job Activities Inventory, an instrument that included ratings of occupational requirements for 27 different job-related abilities. Each ability was rated for its importance to job performance on a 5-point scale with "Not Very Important," "Somewhat Important," "Important," "Very Important," and "Extremely Important" as response anchors. These responses were scored 1, 2, 3, 4, and 5, respectively. Respondents also were offered the choice of "Not Applicable" as a response. This response was treated as missing data and was not used when computing the occupational scores.

This study used the same 8 ability ratings used by Vickers, Hervig, and White (1997). Four of the eight ratings assessed the importance of physical abilities:

> Strength: Ability to use muscle force in order to lift, push, pull, or carry heavy objectives for a short period of time.
>
> Flexibility: Ability to bend, stretch, twist, or reach out with the body, arms, or legs.
>
> Body Balance: Ability to keep or regain one's balance or to stay upright when in an unstable position.
>
> Stamina: Ability to exert oneself physically without getting out of breath.

The total physical demands (PD) of the occupation were measured by averaging the Strength, Flexibility, Body Balance, and Stamina scores for each occupation. The summary measure was computed because ratings of specific physical ability requirements were very highly correlated and defined a single dimension in Reynolds et al.'s (1992) factor analysis of the full set of 27 ratings.

Four other ability ratings were chosen to represent the cognitive and psychomotor ability domains identified in Reynolds et al.'s (1992) factor analysis of the importance ratings. The following items were

chosen to represent "Communication," "Cognitive Ability," "Perceptual Skill," and "Dexterity and Fine Motor Control," respectively:

Oral Communication (OC): Ability to use English words and sentences so others will understand and the ability to understand the speech of others.

Reasoning (R): Ability to understand and organize a problem and then to select a method for solving the problem.

Reaction Time (RT): Ability to give a fast response to a signal (sound, light, picture) when it appears.

Dexterity (D): Ability to quickly make skillful, coordinated movements of the fingers, hands, wrists, arms, or legs.

Each item used as a marker for a general dimension was chosen because it had the highest loading on the factor it represented.

Hospitalization Criteria

Ferguson et al. (1985) classified hospitalizations as due to injury in a two-step process. Initially, a hospitalization was classified as the result of an accident " . . . if the diagnoses were included in the 'Accidents, Poisonings, and Violence' category of the International Classification of Disease, Adapted for Use in the United States, Eighth Revision (ICDA-8)" (Ferguson et al., 1985, p. 80). The second step deleted injuries that were nonaccidental. Specifically, "Injuries were not included that were self-inflicted, combat-related, or the result of an assault" (Ferguson et al., 1985, p. 80). These data are referred to hereafter as the Ferguson data or Ferguson rates.

The results obtained with the overall accident rates computed from the Ferguson data were compared to the results obtained with the overall accident rates determined from the EPISYS computer system (Jaeger, White & Show, 1996, hereafter EPISYS data or EPISYS rates). The objective was to determine whether results obtained with an earlier cohort of sailors could be generalized reasonably to today's U.S. Navy. Differences could occur for several reasons. First, the EPISYS accident rates that Vickers and Hervig (1998) used to establish the association between job demands and occupational differences in accident rates included all hospitalizations categorized as "Accidents, Poisonings, and Violence." As noted above, Ferguson et al. (1985) excluded some hospitalizations falling in that category. The EPISYS rates, therefore, would be expected to be slightly higher than the Ferguson rates, even if the overall population rate for accidents did not really differ for the cohort studied by Ferguson et al. (1985) and the time period covered by EPISYS data. The subcategories excluded by Ferguson et al. (1985) should represent only a small proportion of the total accident rate, so the differences would be expected to be minor. Second, any changes in the ICD codes between ICDA-8 and ICD-9 could affect the rates and their relationship to job demands. Both differences change the definition of "accident," thereby making the replication of earlier findings a useful frame of reference for evaluating the generalizability of the results obtained with the Ferguson data.

Ferguson accident rates were computed from statistics reported in Table 2 of Ferguson et al. (1985). The table reported the average number of personnel in each occupational category during the period of study, the number of injuries occurring on duty, and the number of injuries occurring off duty. The information in the table was translated into illness rates as follows:

Rate = (Number of Injuries/4) * (100,000/Number at Risk)

The number of injuries was divided by four to get the number of injuries per year for the four year period from 1974 through 1977. The second term on the right side of the equation yields rates per 100,000 incumbents per year. These computations yielded accident rate measures expressed in the same units used by Vickers and Hervig (1998). Comparable units simplified the comparison of rates in the two studies and the cross-validation of Vickers and Hervig's (1998) regression equation to predict total accident rates.

Analysis Procedures

The SPSS-PC statistical package (1998) was used for the data analyses. The TETRAD program developed by Glymour, Scheines, Spirtes, and Kelly (1987) was used to test the hypothesis that job demands and accident rates defined a single latent trait of risk taking. Details of specific analysis procedures are provided in the presentation of results.

Results

Replication

The Ferguson data produced results similar to those obtained with the EPISYS data (Table 1):

A. The average Ferguson rate (Mean = 1,161.92; SD = 356.61) was slightly lower than the average EPISYS rate (Mean = 1,199.77; SD = 309.79). The difference was statistically nonsignificant (d = 37.15, t = .99, 56 df, p > .327) despite a moderate correlation between the rates (r = .634, p < .001).

Table 1.

Correlations between Job Demand Ratings and Accident Rates

		Ferguson et al. (1985):		
Job Demands	EPISYS	Total	On Duty	Off Duty
Physical (PD)	.578	.686	.792	.547
Reaction Time (RT)	.361	.324	.241	.315
Dexterity (D)	.232	.287	.227	.273
Reasoning (R)	-.308	-.320	-.193	-.331
Oral Communication (OC)	-.292	-.315	-.292	-.282

Note. N = 57.

B. The pattern of correlations with occupational demands was comparable (Table 1). Physical demands were the strongest correlate of accident rates in each case. The average absolute difference between the Ferguson and EPISYS correlations was .047. The PD ratings produced the largest difference (.108), but even that difference was not statistically significant ($z = 1.35$, $p > .088$).

C. Vickers and Hervig's (1998) regression equation cross-validated well (cross-validation $r = .769$; development multiple $R = .781$). That equation systematically overestimated the Ferguson rates by 52.62 (SD = 230.65) hospitalizations per 100,000 person-years. This bias was only slightly larger than the difference in the averages of the Ferguson and EPISYS accident rates (37.15) and was not statistically significant ($t = .23$, 56 df, $p > .409$).[5]

D. The cross-validated equation was nearly as good as the sample-optimized equation for the Ferguson rate. Applying the identical stepwise regression procedures and criteria employed to develop the Vickers and Hervig (1998) equation to the Ferguson data:

1. The same occupational demands entered the regression equation.

2. The multiple correlation when regression weights were computed from the Ferguson data was only slightly larger than the cross-validation coefficient for the EPISYS regression weights ($R = .794$ vs. $r = .769$).

3. The incremental variance accounted for by estimating four regression parameters de novo in the Ferguson data was statistically nonsignificant (Variance explained = 3.9%, $F_{4,53} = 1.40$, $p > .246$).[6]

Effect of Duty Status

Occupational physical demands predicted on-duty rates more strongly than off-duty rates ($r = .792$ vs. $r = .547$, $z_{Diff} = 3.02$, $p < .002$, one-tailed, by Steiger's [1980] Equation 12). Duty status did not affect the correlations between other job demands and the Ferguson on-duty and off-duty rates (Reaction Time, $z_{Diff} = -0.61$, $p > .270$; Dexterity, $z_{Diff} = -.38$, $p > .351$; Reasoning, $z_{Diff} = 1.13$, $p > .127$; Communications, $z_{Diff} = -.08$, $p > .467$; all *p*s one-tailed).

On-duty accidents produced a simpler regression equation than off-duty accidents (Table 2, p. 10). Only PD and RT were significant predictors of on-duty accidents; the off-duty equation included PD, RT, and R. However, the equation for on-duty accidents was more accurate despite requiring fewer predictive parameters ($R^2 = .662$ vs. $R^2 = .449$, respectively). Residual correlations to other job demand ratings were small and statistically nonsignificant for both equations ($|t| < 1.32$, $p > .192$ for each).

Tetrad Test of Risk Taking Model

Glymour et al.'s (1987) TETRAD program was run to determine whether the data could be explained by a single common factor that gave rise to the set of correlations between PD, RT, on-duty accidents and

Table 2. Equations for Predicting Ferguson On-duty and Off-duty Rates from Occupational Demands

	On-Duty Rate:				Off-Duty Rate:			
	b	SE(b)	*t*	Sig.	*b*	SE(b)	*t*	Sig.
Physical Demands	125.42	12.57	9.98	.001	182.89	38.78	4.72	.001
Reaction Time	35.10	13.41	2.62	.012	120.82	40.79	2.96	.005
Reasoning	N.A	N.A	N.A	N.A	-232.54	93.04	-2.50	.016
Constant	-222.68	54.66	-4.07	.001	932.19	407.72	2.29	.027
R^2	.669					.449		
Shrunken R^2	.657					.417		
SEE	69.32					210.70		

Note. N.A. = Not applicable. Reasoning was not a significant predictor of on-duty rate. Neither Dexterity nor Oral Communication entered any of the equations.

off-duty accidents. The single common factor model would fit the data if exposure to occupational conditions and accident rates were different expressions of a risk taking trait. Two of the three tetrad equations implied by this model differed significantly from zero ($r_{12}*r_{34} - r_{13}*r_{24} = .224$, $p < .017$; $r_{12}*r_{34} - r_{14}*r_{23} = .106$, $p < .043$).[7]

Alternative Models

The TETRAD results did not support the assumption that a single general causal variable could account for the pattern of covariation among the indicators. The correlation and regression analyses established PD and RT as possible common causes of on-duty and off-duty accidents. These two facts were consistent with the claim that occupational demands could be the basis for the correlation between on-duty and off-duty accident rates. In fact, the *pr* between on-duty and off-duty accident rates controlling for PD and RT was in the range that Cohen (1988) would classify as a small effect, but *pr* still was statistically nonsignificant (partial $r = .164$, $p > .230$). When the residual covariation was expressed relative to the total variance in the accident rates (on-duty $sr = .095$; off-duty $sr = .129$).

Further analysis explored the possibility that other models of the relationships were competitive alternatives for the stepwise regression model. Stepwise regression selects the best possible predictor at each of several steps in an analysis. The predictors chosen at each step are contingent to some extent on the predictors selected in prior steps. This stepwise procedure offers substantial opportunity to capitalize on chance and does not constitute a systematic exploration of the full range of possible predictive models. Other sequences of predictor selection conceivably could yield predictive equations with different sets of predictors that were as good or nearly as good as the model produced by the stepwise regression. If such models exist, the focus on a single equation could represent premature closure of the search for the best model to predict on-duty and off-duty accidents. Thus, other models were developed to identify competing alternatives to the results

of the stepwise regression and to provide context for evaluating the model implied by that regression.

The introduction to this report mentioned the possibility that on-duty accidents might contribute to the estimation of the probability or severity of accidents. If so, the causal path from occupational demands to off-duty accidents might lead through on-duty accidents. This possibility would be supported if partialling out on-duty accidents reduced the correlations between off-duty accidents and both occupational demands to zero. In fact, both *sr*s for occupational demands indicated small, but potentially important, direct effects for RT (ES = 3.4%) and PD (ES = 2.6%). The RT association was statistically significant (p = .049, one-tailed), but the PD association was not (p = .075, one-tailed). The discrepancy between the evaluation of these effects based on effect size and the evaluation based on statistical significance arises because the sample is small (Rosenthal & Rosnow, 1984).[8]

Reexamination of the *pr*s available after entering PD ratings into the stepwise regression suggested another possibility. The *pr* between on-duty and off-duty rates was statistically significant after controlling for PD (partial r = .262, $p < .026$, one-tailed). Thus, off-duty accident rates could have been added to the model to predict on-duty rates after entering PD. The resulting model might have been interpreted as indicating that occupational demands for physical exertion and general risk-taking tendencies, indicated by off-duty accident rates, jointly influenced on-duty accident rates.

The (PD+Off-duty) alternative to the (PD+RT) model was a plausible competitor because both models involve two predictors, and each predictor made a statistically significant contribution to the prediction of on-duty accident rates. However, the incremental variance explained by the off-duty accident rates after entering PD was less than the incremental variance explained by RT after entering PD (1.9% vs. 3.7%, respectively). The (PD+RT) model, therefore, had greater overall predictive accuracy than the (PD+Off-duty) model. When two models utilize the same number of parameters, but one predicts a criterion more accurately, the more accurate model is more parsimonious. Mallows' (1973) C_p, a quantitative parsimony index, was lower for the (PD+RT) model ($C_{p(PD+RT)}$ = 3.47 vs. $C_{p(PD+Off\text{-}Duty)}$ = 6.18), thereby indicating greater parsimony for that model.

A further check on the adequacy of the (PD+RT) model was obtained by computing Mallows' (1973) C_p for all possible regression models that would use PD, RT, and one accident rate as predictors of the other accident rate. The C_p for the (PD+RT) model was the lowest for both criteria. Thus, the stepwise regression models were the best representations of the data by this criterion.[9]

Discussion

Three study findings are central to comparing the trait and occupational learning models of risk taking. First, PD and RT entered the regression equations for both on-duty and off-duty accidents. These occupational demands could be common antecedents of both types of accident. Second, controlling for PD and RT produced a statistically nonsignificant partial correlation between on-duty and off-duty accident

rates. Together, PD and RT accounted for more than 94% of the covariance between the accident rates.[10] Third, the TETRAD results were not consistent with a single factor explanation for the pattern of covariation among occupational demands and accident rates.

The findings support the occupational learning model of risk taking. The first finding establishes that the data satisfied a basic condition for inferring that occupational demands are causal antecedents of both on-duty and off-duty accident rates. The second finding is consistent with the assertion that these common antecedents produce the observed correlation between the accident rates. The occupational learning model accounts for these results by assuming that exposure to occupational environments with high PD and RT demands influences the perceived risk of injury, anticipated severity of injury, or both. The third finding rules out any single factor model, including risk taking, as a plausible alternative to the occupational learning model.[7]

The processes that yield occupational learning of risk taking cannot be determined from this study. A plausible basis for occupational learning has been presented by combining the Health Belief Model with the availability heuristic. This model demonstrates that the occupational learning approach can be derived logically from models and constructs that have demonstrated validity in extensive bodies of prior research. However, this study did not directly measure the perceived probability of injury, the perceived severity of injury, or any other psychological process or state that the proposed explanation implies are links between occupational demands and increased accident rates. What the study has demonstrated is that the occupational learning model can account for some empirical findings. This observation changes the status of occupational learning from a purely hypothetical analytic derivation to a model with some empirical support. Further research examining this perspective on risk taking appears justified. The specific mechanisms suggested here as a basis for occupational learning should be treated as just one possible explanation until evidence is available to confirm or disconfirm the implied hypotheses.

Occupational learning is not likely to be the whole story behind the relationships between occupational demands and accidents. As stated, the occupational learning model does not explain why PD ratings were more strongly related to on-duty accidents than to off-duty accidents. The probable explanation for this finding is that physical exertion on the job affects accident rates by two pathways. One pathway involves risk-taking tendencies. The other pathway arises from physiological considerations rather than psychological considerations. PD ratings are a good index of the physical exertion required on a job (Carter & Biersner, 1987). Physical exertion can cause accidents, particularly when the requirements exceed the capacities of the individual (Chaffin, Herring, & Keyserling, 1978). Physical exertion is commonly cited as a cause in U.S. Navy accident reports (Helmkamp & Bone, 1986). The additional predictive power of PD ratings for on-duty accident rates, therefore, may indicate that the PD ratings index both physiological and psychological risk factors.[11]

The occupational learning model also cannot account for the fact that occupations with high reasoning demands have lower off-duty accident rates. This relationship probably is spurious in the sense that reasoning demands do not cause lower off-duty accident rates. Instead,

the association probably arises because both variables are influenced by a person's general intelligence. General intelligence probably is a common cause of exposure to reasoning demands on the job and of accidents in off-duty settings. U.S. Navy selection policies are designed to place more intelligent sailors in those occupations that have high reasoning demands. General intelligence also is associated with lower accident rates in U.S. Navy personnel (Ferguson, McNally, & Booth, 1983). The association to lower accident rates may be partly the result of assignment policies, but it is also reasonable to consider the possibility that people with intelligence have fewer accidents because they are more likely to recognize and avoid risky situations and/or take steps to minimize risks when appropriate. The association between accidents and intelligence may be evident only for off-duty accidents because on-duty conditions constrain the opportunity to express intelligence. The option of avoiding the situation is not available on the job; job design and safety programs may control on-duty risks in ways that reduce the effects of intelligence. If occupational reasoning demands correlated with off-duty accident rates only because both variables share intelligence as a common cause, the association between the two meets Heise's (1975) definition of a spurious correlation.

The study findings appear to justify further investigation of the occupational learning model of risk taking. Efficient development of an accurate understanding of risk taking will require that apparently contradictory evidence found in research on personality development and accident research be taken into account. People typically become less neurotic, more conscientious, and more agreeable with age (Costa & McCrae, 1992; McCrae & Costa, 1990). These changes imply decreases in risky lifestyle behaviors (Vickers et al., 1990). Also, accident rates tend to decrease with age in the U.S. Navy (Ferguson et al., 1983; Helmkamp & Colcord, 1984). All of these facts conflict with occupational learning if such learning implies that risk-taking tendencies increase with longer exposure to a job with heavy physical demands and high reaction time requirements.

The apparent conflicts between occupational learning and other research may be superficial and misleading. First, personality trends may not be relevant to risk taking, even though risk taking often is considered a personality variable. The judgment processes involved in risk taking might be more properly considered cognitive variables. If so, these processes may be more closely related to intelligence constructs than to personality constructs. The developmental pattern for intelligence is not necessarily the same as that for personality, so personality trends would not necessarily apply to judgment heuristics. Indeed, heuristics may be distinct from both intelligence and personality with their own developmental dynamics. The fact that the use of heuristics can be significantly modified by academic training (Nisbett, 1993) is good reason to consider this possibility. Second, not all risky behaviors should be thought of as elements of a risky lifestyle. Risky lifestyle is a term that is commonly applied to behaviors such as overeating, alcohol consumption, nicotine consumption, drug use, and unsafe sex. These behaviors generally share the common attribute of being intrinsically gratifying in addition to causing health problems. Occupational exposure to risk ordinarily will not have this element of intrinsic gratification. For example, not many people would be expected to lift and carry heavy materials for the pure pleasure of doing so.

Given this difference, the argument that changes in personality influence risk on the job is questionable even if those changes do modify the behaviors that comprise a risky lifestyle. Third, declining accident rates do not necessarily mean that older individuals are taking less risk. Older individuals may be less frequently exposed to risk. Perhaps the most physically demanding, dangerous jobs tend to be assigned to relatively junior personnel. If so, a declining accident rate can occur even though older individuals take greater risks. The accident rate will decline if risk exposure drops faster than risk-taking tendencies grow. Finally, the growth curve for risk taking may have multiple components. The initial phase of learning may increase risk as an individual is repetitively exposed to risky situations that either do not produce accidents or only produce minor injuries when accidents do occur. Over time, the individual is increasingly likely to have observed some serious accidents and the associated injuries.[12] Seeing these serious accidents and their consequencies may significantly modify the perception of risk. The possibilities sketched here illustrate how examining the conflicts between occupational learning, personality development, and accident trends may help refine the concept of risk taking and the place of risk taking in a model of accidents.[13]

It might be argued that all of the foregoing points are irrelevant for today's U.S. Navy. Ferguson et al.'s (1985) data covered the period from 1970 to 1974. Accident dynamics conceivably could have changed substantially in the intervening 25 years, thereby making the preceding explanations moot. This suggestion can be countered by the fact that relationships between occupational demands and overall accident rates for the Ferguson data were very similar to those observed with the EPISYS data that were collected much more recently. This similarity suggests that the phenomena involved were stable for 25 years (1970-1994, inclusive). Unless the situation has changed dramatically in the last five years, the findings reported here should generalize to today's U.S. Navy.

The issues in this paper are not merely academic. These issues have important implications for safety programs. Recognizing that the development of risk-taking tendencies extends into early adulthood, then developing an understanding of risk taking based on these developmental processes could improve accident prevention programs. The processes involved may point to nonobvious methods for accident reduction. For example, if judgment and decision heuristics are involved, training in statistical thinking can reduce biases arising from the use of those heuristics (Nisbett, 1993). Considering risk taking in this light, the occupational learning interpretation of the present study findings could change the problem of how to reduce accident rates. Given the earlier assumption that a risk taking trait was a strong influence on accident rates (e.g., Ferguson et al., 1985), the best means of reducing accidents would be to screen out personnel with risky behavioral tendencies or to assign them to low-risk jobs. The occupational learning model implies that training aimed at reducing learned risk-taking tendencies would be the best route to reduced accident rates. Training programs that overcome the negative consequences of judgment and decision heuristics have been successful in other areas (Nisbett, 1993). If future research bears out the present speculation that these heuristics are involved in the development of risk-taking tendencies, the present findings suggest that programs based on these established psychological

phenomena could be a useful addition to the training armamentarium. That inference remains speculative until further studies demonstrate the effects of decision heuristics and the efficacy of programs based on those heuristics.

In summary, this study was undertaken to better understand why U.S. Navy enlisted occupations with high on-duty accident rates also tend to have high off-duty accident rates. The suggestion that occupational experiences teach people to accept risks in off-duty situations was advanced. This hypothesis was based on well-established empirical phenomenon from judgment and decision making research and existing health behavior models. The empirical evidence presented here indicated that occupational demands can account for the correlation between occupational differences in on-duty and off-duty accident rates. This finding establishes a prima facie case for occupational learning as one factor contributing to adult differences in risk taking. The processes by which occupational demands affect accident rates were not directly examined, so further work is needed to test hypotheses about specific mechanisms of influence. Further work also must address the apparent conflicts between these findings and trends in the personality research and accident research literatures. At a minimum, the study justifies adding occupational learning to the topics considered in accident research. The shift from thinking about risk taking as a fixed trait brought to the job to thinking about risk taking as an attribute that develops under the influence of occupational experiences could have important implications. Incorporating this perspective into thinking about risk taking on and off the job may be critical to a sound theoretical understanding of risk taking. An accurate understanding, in turn, implies an improved basis for designing accident reduction programs.

Footnotes

[1]The claim that exposure to hazards increases risk taking may appear counterintuitive. One might expect common sense and formal training to teach a person in a hazardous job to be cautious. The caution learned on the job then might be reasonably expected to generalize to off-duty activities. This argument is not compatible with the available evidence unless an improbable state of affairs exists. High on-duty accident rates indicate relatively frequent accidents. Findings presented by Vickers, Hervig, and White (1997) and replicated in this paper indicate that occupations with high accident rates have intrinsically hazardous job demands. These jobs can be expected to have safety programs to control accident rates. The high accident rates observed for these jobs implies that the hazards are sufficient to cause accidents in spite of the precautions taken to avoid accidents. If off-duty exposure to risks is approximately the same for people in all different occupations, people whose jobs taught them to be more aware of risks and more cautious would have lower than average off-duty accident rates. Jobs with high on-duty accident rates would have lower than average off-duty accident rates. The combination of high on-duty accident rates with low off-duty rates would produce a negative correlation. The observed correlation is positive, so it is unlikely that job hazards teach caution.

[2]Other mechanisms can be identified, even if the search is limited to judgment and decision heuristics. For example, the representativeness heuristic could affect the subjective probability that performing a risky task will result in accidents. When a person uses a representativeness heuristic to make judgments, he or she anticipates that engaging in a given activity will produce the result that has been most commonly associated with that activity in the past. The fact that the result is the most common outcome of the activity is the basis for characterizing it as representative of the activity. Given a low base rate for accidents, the representativeness heuristic will lead to the judgment that no injury will occur in risk situations. The effect on accident rates will be the same as that of the availability heuristic because the representativeness heuristic will reduce the expectation of a negative outcome.

The correct specification of the specific mechanism(s) by which occupational experiences influence accident rates is not the immediate objective of this paper. Instead, this paper presents the argument that exploring such mechanisms should be part of accident research. The existing focus on risk taking as a preexisting personality trait may result in missed opportunities to better understand accident rates. Occupational influences on risk taking have been alluded to in the literature (Hansen & Pedersen, 1997), but the position has not been systematically developed. This paper emphasizes arguments grounded in existing empirical results to increase the plausibility of this line of inquiry. The reliance on explanatory mechanisms that have been demonstrated to be useful in previous research on health behavior, judgment, and reasoning constrains the construction of the alternative scenario, thereby making the occupational learning rationale something more than a purely intellectual exercise.

Ideally, this paper represents the first step in a sequential development of the occupational learning approach to risk. This step consists of showing that well-documented judgment mechanisms can be invoked to predict that risk taking can be learned on the job. The empirical evidence presented in this paper then demonstrates that at least one general prediction derived from the learned risk-taking perspective holds true for accident data. This demonstration helps justify further study of the psychological processes and mechanisms involved in making judgments about risk.

[3]Even though risky tasks are completed safely in most cases, injuries do occur. If a person recalls an instance or instances of injury, the recollections must be combined with recalled instances of noninjury in some way. One possibility is that the judged risk of injury will be based on some subjective weighted combination of recalled injuries and recalled accident-free task performance. Another possibility is that other decision heuristics will be employed. For example, injury may be discounted as not representative of the typical events (Tversky & Kahneman, 1974).

[4]Estimates of outpatient treatment rates are available from several prior studies. Doll, Rubin, and Gunderson (1969) reported 5.61 sick call visits per 1,000 crew members per day in a study of an attack cruiser. Rahe, Mahan, Arthur, and Gunderson (1970) reported rates of 9.6, 9.7, and 5.7 sick call visits per 1,000 crew members per day in a study of three cruisers. Rubin, Gunderson, and Arthur (1971) reported a sick call visit rate of 11.7 per 1,000 crew members per day in a study of a battleship. Nice and Hilton (1990) reported rates for destroyer tenders, submarine tenders, oilers, repair ships, and salvage ships. Data were reported by ICD-9 code for males and females separately. Using the data for males to provide the closest correspondence to the earlier studies, sick call rates for the ICD-9 categories analyzed in this paper totaled 318.7 visits per 1000 crew members per month (i.e., approximately 10.6 per day). The various rates reported in these studies translate to between 204,765 and 427,050 visits per 100,000 crew members per year. The total rate for the present study was 8,800 hospitalizations per 100,000 per year, thereby indicating that there were 23.3 to 48.5 times as many outpatient treatments as hospitalizations. In Nice and Hilton's (1990) data, accidents accounted for approximately 30% of the total number of visits. Applied to the range of total outpatient visit rates estimated here, this figure would result in 61,430 to 128,115 accident cases per 100,000 crew members per year. If 10% of these outpatient accident cases resulted in duty limitations, the total number of cases involving unavailability for work would be 4 to 9 times the number of hospitalization cases (i.e., 6,143 to 12,812 outpatient cases vs. 1,385 hospitalization cases). Illnesses treated on an outpatient basis are milder than those requiring hospitalization. The typical amount of time lost from duty probably is one or two days (Krentz, Li, & Baker, 1997). However, because of the much higher frequency of these accidents, the total time lost to injuries that are treated on an outpatient basis can be expected to be a significant component of the overall time lost due to accidental injury. The figures cited here must be interpreted cautiously. The estimates do not allow for differences between ship and shore illness rates and cover only some types of ships (i.e., cruisers, battleships, and aircraft carriers). Even with these limitations, the

figures illustrate that ignoring outpatient treatment will significantly underestimate the cumulative illness/injury burden.

[5]The apparent bias was partly attributable to the fact that only 57 of the 59 occupations used to develop the equation were studied here. When the residuals for the original equation were examined for those 57 occupations, the average error was -14.77 (SD = 220.61). Using this value as a reference point, the observed bias in this replication (Mean = -52.62) represents an increase of only -37.85. This bias represents 3.3% of the average hospitalization rate. However, even this estimate of bias may be misleading. Case-by-case examination of the data indicated that one outlier had an extremely low predicted total accident rate relative to its observed rate (residual = -864.37). Dropping that case from the computations, the average cross-validation residual was 0.40 (SD = 190.25). The average residual was not significantly different from zero in the full sample (t = 0.07, 56 df, p = .947, two-tailed) or with the outlier deleted (t = 0.002, p = .998, two-tailed). The overall pattern of evidence unequivocally indicates that the initial equation for predicting total accident rates cross-validated well in the Ferguson et al. (1985) data.

[6]The equation was Total Accident Rate = 817.03 + (306.37 * PD) + (156.48 * RT) + (259.40 * R). Standard errors for these four regression constants were 446.06, 42.43, 44.63, and 101.79, respectively.

[7]Tetrad equations have been used to evaluate substantive models for some time. For example, the earliest article dealing specifically with tetrad equations in the PsycLit® data base is Thompson (1927). However, because these equations are not widely used today, it is useful to sketch their rationale and application to testing the hypothesis that several indicators are manifestations of a single underlying factor.

The single factor version of the general tetrad rationale proceeds as follows: Suppose a single underlying causal factor generates a set of observed correlations. The causal influence of the underlying factor can be expressed as a quantitative value (i.e., the factor loadings estimated when a single factor is extracted) for each indicator variable. Any pair of indicator variables will be correlated only to the extent that they share the underlying factor as a common cause. If this were not true, more than one common causal factor would be present, a condition contrary to the assumption that a single common factor is present. Because the single underlying factor is the only common cause affecting any pair of indicator variables, the correlation between two indicators is determined by the strength of the causal effect on each indicator. The correlation is the product of the strengths of the two causal effects (i.e., the product of the factor loadings) for the indicators. It follows that the product of two correlations is the product of the four factor loadings. Different pairs of correlations can be chosen that involve the same four indicator variables. For example, the pair r_{12} and r_{34} would involve indicator variables 1 through 4, but so does the pair r_{13} and r_{24}. If the single factor model is correct, pairs of correlations that involve the same four indicator variables will yield identical products. Note that all of these assertions are conditional on the truth of the assumption that a single factor is present.

Tetrad equations are produced by choosing appropriate pairs of correlations. Two pairs of correlations are chosen that involve four different correlations representing associations between four different indicator variables as indicated in the preceding paragraph. The difference between products of the pairs of correlations then is computed. This difference is a tetrad difference. The tetrad difference then is tested to see whether it differs significantly from zero given the sampling variability. Following standard statistical logic, if a tetrad difference is too deviant from zero to be attributed to sampling variability, the difference is regarded as statistically significant. Even one significant difference provides a basis for rejecting the single factor model, because that model implies that all tetrad differences will be equal to zero.

The preceding verbal arguments can be rendered mathematically in the following assumptions and equations. Suppose a single factor is represented by four indicator variables, x_1 to x_4. The factor loadings for the four indicators are *a*, *b*, *c*, and *d*, respectively, and represent the causal influence of the underlying factor on the indicators. No pair of indicators shares any other common causal influence. Then:

$$r_{12} = (a*b)$$
$$r_{34} = (c*d)$$
$$r_{12}*r_{34} = (a*b*c*d)$$

At the same time,

$$r_{13} = (a*c)$$
$$r_{24} = (b*d)$$
$$r_{13}*r_{24} = (a*c*b*d) = (a*b*c*d)$$

so

$$r_{12}*r_{34} = r_{13}*r_{24} = (a*b*c*d)$$

and

$$r_{12}*r_{34} - r_{13}*r_{24} = 0.$$

The sampling variability of tetrad differences can be estimated from sample data (Glymour et al., 1987). The size of the observed tetrad difference can be compared to this sampling distribution to determine whether the difference is too large to be dismissed as a likely product of chance.

A given model can generate multiple tetrad equations. The single-factor, four-indicator case yields three such equations. All of the equations must be tested to evaluate the model. The strict logical implication is that the model is false if the null hypothesis can be rejected for even one tetrad equation implied by the model. In the present instance, two of the three implied equations differed significantly from zero.

Glymour et al. (1987) describe tetrad procedures and the rationale for their use in analyzing causal models in detail. Their TETRAD program provides a tool for examining all of the tetrad equations that can be constructed from a given data set and testing each for statistical significance. This logic and tool, therefore, were used to test the generic hypothesis that a single underlying causal factor could account for the observed pattern of covariation between the PD, RT, on-duty accident rate, and off-duty accident rate. The risk taking factor invoked by Ferguson et al. (1985) is a special case. This interpretation is a special case because it provides a particular interpretation of the hypothesized underlying single factor. Other interpretations might apply to the single factor even if it existed. The tetrad tests simply indicate whether a single factor model is consistent with the data; they do not indicate what the factor is if the model fits. This point is noted because it means that the present analyses not only make a case against the risk taking model, but also can be used to argue against any other single factor model.

[8]Partial and semipartial correlations have an important difference that must be considered when using them to evaluate alternative models. Cohen and Cohen (1983) note that the *sr* " . . . equals that proportion of the Y variance accounted for by X_i beyond that accounted for by the $k - 1$ IVs [independent variables]" (p. 101). The *pr* " . . . is the correlation between that portion of Y that is independent of the remaining variables . . . and that portion of X_i that is independent of the [same] remaining variables" (p. 102). The effect of this difference is that the *sr* expresses the unique variance explained by predictor X_i relative to the total variance in Y. The *pr* expresses that same unique variance relative to the residual variance in Y. In stepwise regression procedures, the residual variance and the residual degrees of freedom for the equation are the basis for estimating the mean squared error following the entry of predictor X_i into the equation. The statistical significance of X_i depends on the amount of unique variance explained by X_i relative to this residual mean squared error. The significance test for X_i, therefore, is directly related to the *pr*. However, except in those rare cases in which the residualized variable is the focus of theoretical concerns, Y is the variable to be explained by the model. The unique contribution of X_i to this explanation is indicated by the *sr* because that correlation is based on the total Y variance. The *prs* and *srs*, therefore, provide different information. The former indicates the statistical significance of the incremental predictive accuracy of X_i; the latter indicates the unique predictive or explanatory power of X_i relative to the variable of interest for practical and theoretical purposes.

The inferences drawn from significance tests based on the *pr* and the *sr* can differ. The *pr* is the basis for inferring that X_i explains a greater than chance proportion of the residual variance in Y; the *sr* is the basis for inferring that the effect of X_i is large enough to explain an important amount of the variation in Y. The former inference can be correctly drawn in instances when it would be incorrect to draw the latter inference. In general, "It can be seen that [the squared pr] will virtually always be larger than and can never be smaller than [the squared sr], because [the squared sr] is the unique contribution of X_i expressed as a proportion of the *total* Y variance whereas [the *pr* squared] expresses the same unique contribution of X_i as a proportion of that *part* of the Y variance not accounted for by the other [independent variables]" (p. 102, italics in original). Because of the difference

between the total Y variance and the part of the Y variance not explained by other independent variables, it is possible for the unique variance explained by X_i to be statistically significant, but trivial in absolute magnitude.

To illustrate the potential for conflicting interpretations when considering the *sr* and the *pr*, consider an extreme example. An analysis is conducted with the objective of determining the value of a predictor, *p*, relative to a criterion, *c*, after controlling for one or more other variables. Suppose the variables that have been controlled accounted for 99% of the variance in *c*. Suppose further that the *pr* accounts for 50% of the residual variance (i.e., partial r = .7071). This partial correlation provides the basis for a meaningful significance test. The significance test can be constructed by comparing the residual variance explained to the mean squared error computed by dividing the residual variance (0.50% of the total variance) by the remaining degrees of freedom. If the ratio is large, *p* explains a greater than chance amount of the residual variance. Given the circumstances specified in this example, the *pr* will be statistically significant even in small samples (i.e., $n \geq 8 + k$, where k is the number of variables partialled out). However, the *sr* will be only semipartial $r = .0707$ (i.e., 50% of 1% is 0.50% of the total variance). This figure is one-half of the 1% minimum proposed by Cohen (1988) for a small effect size. The net result in this extreme example is that it would be correct to infer that the observed covariation was greater than expected by chance, but incorrect to infer that the unique contribution of *p* was large enough to be practically or theoretically important. The latter point is more important than the former when constructing parsimonious models of *c*. Less extreme instances of this general situation arise in the data analyzed in this study.

[9]Mallows' (1973) C_p is a parsimony index based on the explanatory power of the model relative to the number of parameters in the model. In the present comparison, both models involved two predictors for off-duty accident rates. Both models, therefore, required the estimation of three statistical parameters (i.e., two regression weights plus an intercept). The larger R^2 for the (PD+RT) model meant that this model accounted for more variance than the alternative using the same number of parameters. A greater variance accounted for using the same number of parameters implies the larger shrunken R^2 and smaller C_p values. The application of C_p leads to the choice of the model with the greater explanatory power given a fixed number of parameters.

More general comparisons contrasted the PD and RT model with all other possible models that could be computed using PD, RT, and one accident rate as predictors of the other accident rate. These equations, therefore, ranged from single predictor to three predictor models. The C_p of 3.47 for the PD and RT model was the lowest value obtained for any model for both on-duty and off-duty rates. This C_p value approached the minimum possible value for a three-parameter model (i.e., 3.00, cf., Draper & Smith, 1981).

[10]The estimate that occupational demands accounted for more than 94% of the overlapping variance in the accident rates was derived from the difference between the variance explained by the bivariate correlation and the variance explained by the *srs* controlling for PD and RT. The bivariate correlation between the accident rates was $r = .567$, so the overlapping variance was 32.1% of the total variance in each dependent

variable. The *srs* indicated that on-duty accidents accounted for 1.7% of the variance in off-duty accident rates controlling for PD and RT, while off-duty accident rates accounted for 0.9% of the variance in on-duty rates controlling for PD and RT. This residual covariance amounted to 5.3% and 2.8% of the original covariance, respectively. Thus, partialling out PD and RT accounted for 94.7% of the original covariance with on-duty rates as the dependent variable and 97.2% of the original covariance with off-duty rates as the dependent variable. The *srs* differed in size because PD and RT explained different amounts of the total variance in on-duty and off-duty rates.

[11]The difference between the on-duty and off-duty correlations for PD ratings could be explained by amending the occupational learning model. A generalization gradient for learned risk-taking tendencies could be added. The new assumption would be that prior experiences will be applied to the judgment of new situations only to the extent that the old and new situations are psychologically similar. Any differences between the situational cues available at work and away from the workplace then would reduce the relevance of workplace learning for off-duty activities. Such differences, therefore, would reduce the size of the causal effect of occupationally-learned risk taking on off-duty accidents.

Adding a generalization gradient will not account for the overall pattern of findings in this study. If a gradient existed, it reasonably could be expected to apply to all occupational demands. The fact that only the PD ratings produced a significant difference in correlations to on-duty and off-duty accident rates is contrary to this expectation. Of course, the occupational learning model could be amended further to predict that only some occupational conditions would show a generalization gradient. This line of attack would be questionable because it could lead rapidly to a fairly complex model with a number of condition statements regarding the presence and magnitude of generalization effects for different occupational conditions. The availability of a simple alternative model based in research findings from other areas of research on human behavior makes it reasonable to choose the more parsimonious alternative until there is stronger evidence that revisions of the occupational learning model are needed.

[12]The low base rate for serious accidents is the key to this interpretation of the occupational learning process. The learning process also may be more complex than suggested here. Because severe accidents are rare, the likelihood that a person will experience or observe a severe injury early in his or her career may be small. Initially, therefore, occupational experiences may generate many examples of risky or demanding tasks performed without injury. As argued in this paper, this trend could increase the person's general tendency to take risks. However, the probability that a person will observe or experience one or more serious accidents increases as time passes. When those rare events occur, they are likely to become vivid memories. Even a small store of vivid memories of accidents that produced significant injuries might counteract a large store of memories of successful task completion. For example, those memories may be very easily recalled. If so, the availability heuristic that has been employed here to predict learned risk taking could be invoked to predict learned caution. The result is that occupational exposure to risky tasks might produce an initial period of learning to take risks, followed by increased learning of caution as exposure to these rare events increases. Because recruits are young and

typically stay in the service only a short time, at any given time, the great majority of individuals may be in the risk learning phase of the overall process at any given time.

As a rough index of the legitimacy of the sequential occupational learning rationale sketched in the preceding paragraph, consider the following example: If the adage "Once burned, twice shy" is applied to both direct experience and the vicarious experience provided by observing someone else's serious injury, being injured or observing a serious injury may be critical to learning caution. Define a serious injury as one that results in hospitalization. Then, serious on-duty accidents occur at a rate of approximately 237 per year in a population of 100,000 sailors when all occupations are considered. The rate increases to 396 per 100,000 sailors per year for occupations in the top 10% of the distribution of occupational accident rates. The rate reaches a peak of 507 per 100,000 sailors per year in the U.S. Navy occupation with the highest accident rate (Ferguson et al., 1985).

As an illustration, suppose a typical sailor has a network of work colleagues and friends comprised of 50 people. Each year of a sailor's career then provides the sailor with 50 person-years of observation. Given the accident rates specified in the preceding paragraph, the probability that any one person in a sailor's reference group will be seriously injured is p = .00237, .00396, and .00507 depending on whether he is in an average job, a job in the top 10% for risk, or the highest risk job, respectively. Given these probabilities for an individual, the probability that none of the 50 people in a sailor's network will be injured in any given year are p = .888, .820, and .776 for the three jobs. If the probability of an accident occurring in one year is independent of the probability of an accident in other years, the probability that a sailor will complete a four-year enlistment without having a network member seriously injured is p = .622, .452, and .362, respectively. In other words, under these assumptions, roughly two out of every three sailors in the average risk occupation will have no serious injuries to take into account at the end of a 4-year enlistment. Only about one in three sailors will have such an event to take into account even if they are in the occupation with the highest accident rate. If a high risk job is defined as one that falls in the top 10% for accidents, about one out of every two sailors will not experience an accident in his 4-year term of enlistment.

The foregoing example illustrates that the proportion of sailors who have even one serious injury to take into account when judging risks may be small even in jobs involving moderate to high risk. Naturally, the specific numbers provided are contingent on the assumptions and definitions used in the example. The proportions of people who have a serious injury to consider would increase if the size of the reference group were increased or if the definition of a serious accident were lowered. However, the occurrence of a single incident may do little to alter subjective probabilities. Except in cases of major accidents that affect large numbers of crew members at once, no sailor is likely to experience very many instances of knowing someone who is severely injured on the job during a typical 4-year term of enlistment. This fact is reason to believe that much of what is learned by the typical sailor is that it is safe to take risks even in a high risk occupation.

[13]One explanation that might be suggested is that occupational learning should occur only among personnel in risky occupations. This explanation is reasonable assuming risky conditions must be present to learn risk taking. If occupational learning of risk taking were limited to a subset of risky occupations, an overall downward trend in accident rates with age could be explained by assuming that only a few occupations involving a small percentage of the total population were hazardous enough to increase risk taking as individuals got older. The increased risk taking in this small minority of the population then could be offset by increasing caution with age in the large majority of the population. This explanation does not appear relevant to the age-accident rate association in U.S. Navy personnel for two reasons. First, back injury data suggest that more than 40% of U.S. Navy entry-level enlisted occupations involve high risk levels (Vickers et al., 1997). This high proportion of risky occupations would make it unlikely that risk taking would be learned in only a small percentage of the overall population. Second, accident rates decrease with age even in high risk occupations (Ferguson et al., 1983; Helmkamp & Colcord, 1984). This trend is consistent with the view that people learn caution with age even in high risk occupations. Given these considerations, it is more reasonable to explain the age trends in accident rates by assuming that risk exposure decreases, that the probability of observing serious injuries increases, or some other similar mechanisms than by assuming that only some occupations teach risk taking. It is more reasonable to assume that all occupations can teach risk taking. The extent and rate of learning depend on the risk level in the job. The resultant risk taking tendencies at any point in a person's career is determined by the balance between the occupational learning effects and the influence of other factors that decrease risk taking as one ages.

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U.S. Navy occupations with high on-duty accident rates also tend to have high off-duty accident rates. This association has been interpreted as evidence that some occupations attract personnel whose personality profile includes greater than average risk taking. This paper compared this personality trait interpretation with an alternative occupational learning interpretation that assumed that on-duty exposure to risks can teach risk taking. The evidence indicated that: (1) Occupational physical demands and reaction time demands predicted both on-duty and off-duty accident rates. (2) The partial correlation between on-duty and off-duty accident rates controlling for those two occupational demands was statistically nonsignificant. (3) A single factor model, such as that implied by the risk taking trait perspective, did not fit the data. The findings supported the view that occupational experiences are one basis for learning to take risks both on-duty and off-duty.

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